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Modelling soil erosion response to sustainable landscape management scenarios in the Mo River Basin (Togo, West Africa)

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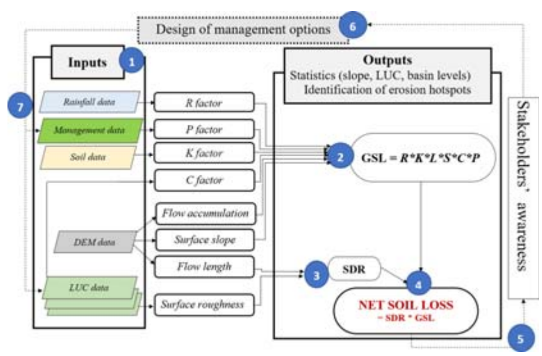
HIGHLIGHTS

- Soil loss at basin scale was evaluated using a spatially explicit RUSLE-based model
- Efficiency of different landscape management scenarios was studied.
- Participatory approach was used to evaluate simulated soil erosion at landscape level.
- Simulated net soil loss was higher than the tolerable limits for the Tropics.
- Controlling erosion hotspots could help reduce the net soil loss up to 70% in the Mo basin.

GRAPHICAL ABSTRACT



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ABSTRACT

The rural landscapes in Central Togo are experiencing severe land degradation, including soil erosion. However, spatially distributed information has scarcely been produced to identify the effects of landscape pattern dynamics on ecosystem services, especially the soil erosion control. In addition, relevant information for sustainable land and soil conservation is still lacking at watershed level. On this basis, using the LAndscape Management and Planning Tool for the Mo River basin (LAMPT_Mo), we (1) modelled soil erosion patterns in relation with land use/cover change (LUCC), land protection regime, and landforms, and (2) examined the efficiency of landscape redesign options on soil erosion amounts at basin scale. We found that Simulated historical net soil loss (NSL) for the Mo basin were approximately 26, 23, 27, and 44 t/ha/yr, for 1972, 1987, 2000, and 2014, respectively. These simulated NSLs were higher than the tolerable soil loss limits for the Tropics. Steep slopes (≥15°), poorly covered lands (croplands and savannas), and riversides (distances ≤100 m) are critical areas of sediment sources. The local appraisal of soil loss was in line with the simulated outputs even though quantification was not accounted for when dealing with rural illiterate people. Furthermore, results showed that the examined management measures, such as controlling the identified erosion hotspots through land protective measures, could help reduce the NSL up to 70%, to values closer to the tolerable limits for the Tropics. The model implementation in the basin showed insights for identifying erosion hotspots and targeting soil conservation planning and landscape restoration measures.

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1. Introduction

Over recent decades, the rapid land degradation is a global environmental threat seriously compromising ecosystem services provision in multifunctional landscapes and reduces the resilience and food security (MEA, 2005; Oladele and Braimoh, 2011; Stockmann et al., 2015; Rhodes, 2014). As a dimension of land degradation, soil erosion is a natural process inducing both on-site impacts (i.e. loss of soils and nutrients especially in agricultural lands) and off-site impacts (i.e. sediment deposition on crop fields, sedimentation of reservoirs, water pollution, etc.) at different extents (Zhang et al., 2017). Water-induced soil loss is understood as soil particles' depletion due to water effects through surface runoff, rill and inter-rill, and gully (Martin-Fernandez and Martinez-Nunez, 2011; Shoshany et al., 2013). Globally, the total land area affected by soil erosion by water is estimated to 1094 Million ha (Lal, 1993) while about 10 Million of ha of croplands are lost annually due to soil erosion in the world (Pimentel, 2006). It is controlled by various factors such as climate, topography, vegetation cover and human interventions (Wischmeier and Smith, 1978; Renard et al., 1997; Tamene et al., 2006). Human interferences, especially improper land management and agricultural practices, deforestation, and other factors, have been mentioned as factor accelerating the natural process of soil erosion (Zhang et al., 2017).

Depending on the extents and intensity of contributing factors, soil loss becomes net when erosion rates become greater than the soil formation rate which vary depending on different bio-climatic conditions. Soil erosion may be assessed using different methods on various scales and targeting different management objectives. Formerly, the quantity and extent of existing soil erosion in the field may be directly determined at the fields, sub-catchments and/or catchment scales by measuring the removed soil or the change detection in soil level in the field (El-Swaify et al., 1982; Hudson, 1971). Nowadays, modelling has supplanted the traditional time-consuming methods of soil monitoring regarding long-term perspectives and many other spatial considerations (Ouyang et al., 2010). In addition, modelling overcome the challenges related to the effects of plot and ecosystem characteristics, and many other time and space related issues (Boix-Fayos et al., 2007). Modelling soil erosion is an efficient method for simulating the extent and intensity of soil erosion, identifying the spatial patterns of sediment sources and deposition sites.

Previous many studies have assessed soil erosion patterns and dynamics at watershed level in relation to landscape conditions, including land use types, landforms, and management practices (Zhou et al., 2014). Soil and Water Assessment Tool (SWAT, Neitsch et al., 2011) has been used to assess soil erosion and sediment yield in Yellow River basin (Hao et al., 2004). The Universal Soil Loss Equation (USLE) and its derivatives (Renard et al., 1997) is among the most commonly used. More RUSLE based applications are evolving in large and complex landscapes (Zhou et al., 2014; Le et al., 2012; Tamene et al., 2014; Tamene and Le, 2015). The low input parameters and its easier implementation in various environments enhance the selection of RUSLE and derivatives (Ashiagbor et al., 2013; Le et al., 2012; Lu et al., 2004; Tamene et al., 2014). It can be implemented in a geographical information system (GIS) environment and be coupled to other spatial explicit models (SEMs) to represent soil erosion. For instance, the Landscape Planning and Management Tool (LAPMAT) is a spatially distributed model based on RUSLE and the sediment delivery ratio (SDR) (Tamene et al., 2014). Other many models such as EROSION 3D (Schmidt, 1990), Water and Tillage Erosion Model and Sediment Delivery Model (WaTEM/SEDEM), Soil and Water Assessment Tool (SWAT), Morgan-Morgan-Finney (MMF) (Morgan & Duzant, 2008; Morgan et al., 1984), Water Erosion Prediction Project (WEPP) (Nearing et al., 1989; Flanagan & Nearing, 1995), Unit Stream Power-based Erosion/Deposition (USPED) (Mitasova et al., 1996) have been used to represent the spatial distribution of the erosion phenomenon.

The wide array of models represents soil erosion through methods and equations describing the link between contributing parameters that offer better explanations of its occurrence. They facilitate the examination of potential advantages and evaluation of the effectiveness of soil conservation measures (Tamene et al., 2014). However, the complexity in representing erosion phenomenon and huge data requirements is still a common challenge to overcome in data paucity (De Vente et al., 2005). This compels to the usage and development of new user-friendly models and tools with less data-demand in order to facilitate evaluation and implementation of management options that fit stakeholders needs and resources, and allows a better understanding of the patterns of the modeled phenomenon (Le et al., 2012; Verburg et al., 2013; Rhodes, 2014). Practically, quantitative spatially explicit information on soil erosion patterns and intensity on a basin scale contributes substantially to landscape management planning and conservation.

In Togo, although studies have been conducted to assess the effects of landscape dynamics on ecosystem services (Folega et al., 2015; Diwediga et al., 2017a; Diwediga et al., 2017b), there has been no assessment of soil erosion and the effects of landscape dynamics on its patterns in rural multifunctional landscapes of Togo. In mountainous landscapes of the Mo River basin, spatial information on soil erosion for the development proper management strategies are still lacking, even though the quantitative spatial assessment of soil loss is important at basin scale where local initiatives can be promoted in effective ways. In this regard, this study aims at contributing to the evolvement of spatial information towards sustainable rural landscapes in Togo. Specifically, the study aims at (1) providing spatially explicit assessment of soil erosion response to landscape patterns in the Mo river basin using the LAMPT_Mo (LAndscape Management and Planning Tool for the Mo River basin); and (2) evaluating the efficiency of some potential land management options for controlling soil erosion. The outcomes of this study are expected to contribute in shedding light on the correlation of landscape patterns and soil erosion and improving the availability of spatially explicit information for the promotion of integrative rural landscape monitoring.

2. Materials and methods

2.1. Study area

The study is carried out in the Mo river basin in the central part of Togo (Fig. 1). The Mo river basin at the Mo outlet (hereafter Mo basin) is a sub-unit of the Volta basin (West Africa). Its total area is approximately 148,592 ha. It is located between 0°–1°E and 8°–9°N. The climate is tropical sub-humid characterized by a rainy season from April to October (Petit, 1981). The mean annual rainfall in the area is between 1200 and 1300 mm with an irregular spatial-temporal distribution. The mean minimum and maximum temperatures reach 19 °C in January with the Harmattan winds and 30 °C in April. The vegetation is characterized by a mosaic of dry and riparian forests, woodlands, Guineo-Soudanian savannahs, and agro-ecosystems within a non-protected zones (Wala et al., 2012; Diwediga et al., 2015). The relief is hilly and rugged and altitude reaches 800 m, especially in Aledjo Mounts. The rivers/streams network is heavily developed in accordance with the rugged topography, making the basin sensitive to hydrological processes, such as soil erosion. The study area covers three protected areas (PAs): Fazao-Malfakassa National Park, Aledjo Wildlife Reserve, and Kemeni Forest Reserve. The prominent environmental issues are land degradation due to overgrazing, unsustainable agricultural land use, fuel wood harvesting, and charcoal production (Aboudou, 2012; Fontodji et al., 2011; Fontodji et al., 2009).

2.2. Brief description of LAMPT_Mo and its specificities

LAMPT_Mo is a clone version of the LAPMAT (Tamene et al., 2014) adapted to the Mo River watershed. Soil erosion modelling in LAMPT_Mo is fundamentally based on the RUSLE model (Renard et al.,

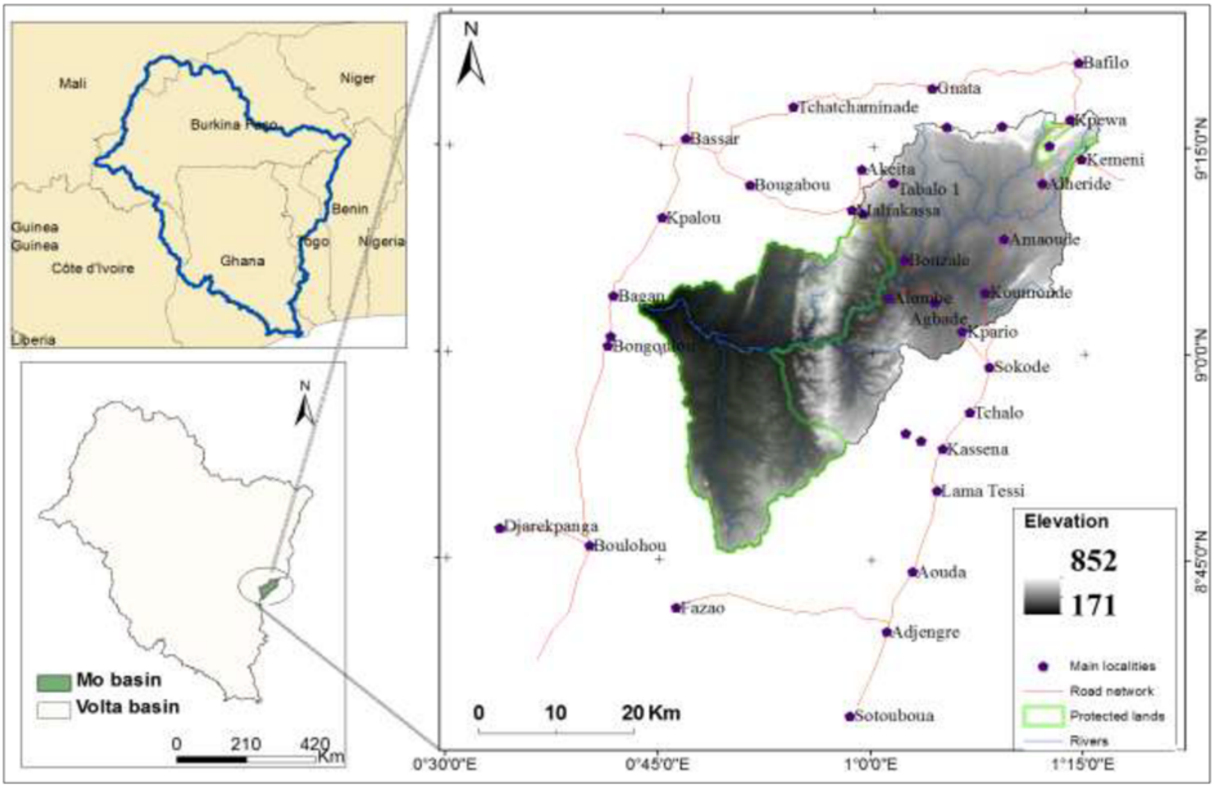

Fig. 1. Location of the Mo watershed in Central Togo.

1997) and implemented in a tropical rural mountainous area. In addition, a sediment delivery ratio (SDR) sub-model is used to represent the spatial patterns of net soil sediment distribution and yield at the basin level. It is implemented in the programming framework NetLogo v5.2 (Wilensky, 1999) for adapting the sub-models. It integrates general features of the landscape (LUC units, landform parameters, soil types, and land use and management options) and rainfall data to simulate gross soil loss, SDR, and the net sediment yield. Contrary to the original model, LAMPT_Mo is calibrated to a multifunctional landscape including large protected areas and agricultural landscapes. It also has the particularity of integrating historical LUC data relevant for evaluating the soil erosion response to historical LUCC. In addition, LAMPT_Mo builds a default land management-supporting factor (P factor in RUSLE) based on a layer of PA networks of the Mo river basin. In term of outputs, the clone model presents soil loss amounts according to the land management regime (PA vs UPA), LUC types (forests, woodlands, savannahs, and croplands), and the proximity to river/streams (buffer zones). The steps and major sub-models of the LAMPT_Mo are provided in Fig. 2. The graphical user interface and features are detailed in the supplementary file (Fig. S1).

2.3. Sub-models for estimating potential, gross, and net soil losses

The potential soil loss risk is derived based on the Sediment Transport Capacity Index (STCI). STCI is a modified LS of the RUSLE model used to map the potential risk of soil loss at the landscape level. As a function of the upslope area (*As*), the slope, and its characteristics, i.e., the slope-length (δ) and slope steepness (α) coefficients (Eq. (1)), STCI does not consider sediment deposition (Tamene, 2005). The particular interest of STCI resides in its capability to identify the most susceptible or vulnerable areas to soil erosion for developing conservation measures at the landscape level (Tamene, 2005). Elevation from the Shuttle Rada Terrain Mission (SRTM) data were used to derive terrain-based parameters required in Eq. (1). Details on the derived parameters for the Mo basin can be seen in Diwediga et al. (2015) and Diwediga et al. (2017a).

$$STCI = \left(\frac{10A_s}{22.13}\right)^{\delta} \times (\delta+1)\left(\left(\frac{\sin(slope)}{0.0896}\right)^{\alpha}\right) \quad (1)$$

Next, the STCI is combined with other soil loss factors different from the LS to predict the gross soil loss (GSL) and its spatial patterns in the Mo basin for the different periods of study and the different land management options at the landscape level. It aims at identifying the most erosion-prone areas, taking into account natural terrain and climatic conditions, as well as the human interferences on soil erosion susceptibility. However, as such, the predicted GSL (Eq. (2)) does not consider the sediment deposition dimension.

$$GSL = STCI\ (KCPR) \quad (2)$$

where *GSL* represents the potential long-term average annual soil loss (in t $ha^{-1}\,yr^{-1}$). *R* (MJ mm $ha^{-1}\,h^{-1}\,yr^{-1}$) is the rainfall and runoff factor by geographic location. The greater the intensity and duration of the rain storm, the higher the erosion potential. *K* is the soil erodibility factor (t ha h $ha^{-1}\,MJ^{-1}\,mm^{-1}$). *C* is a dimensionless factor for the soil cover-management. *P* is the dimensionless factor expressing the support practices of soil management, such as terracing, stone lines, strip cropping, etc.

C factor is developed using the land use cover maps of the study area (Diwediga et al., 2017a). R and K factors used in this study are derived from Diwediga et al. (2017a). P factor is set to a default value of 1 since no supporting land management practice is perceptible in the study area.

To take sediment deposition into consideration, LAMPT_Mo has been designed to estimate the net soil loss (NSL) from the gross soil loss. NSL_i at a pixel scale was computed based on the Eq. (3) (Le et al., 2012, 2012; Tamene et al., 2014). The SDR at the pixel level (SDR_i)

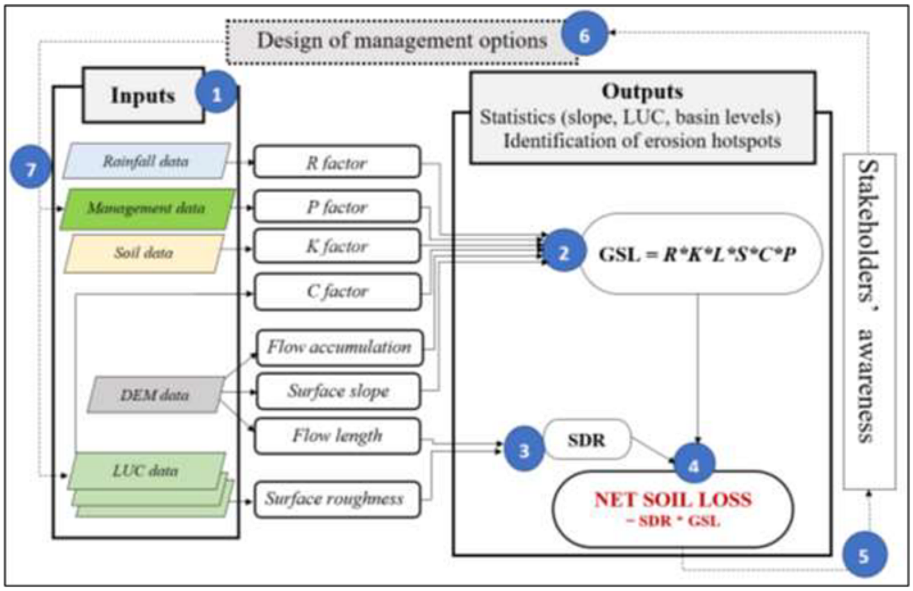

Fig. 2. Process of soil loss modelling in the LAMPT_Mo. Source: adapted from Tamene et al. (2014).

(Eq. (4)) is used as a sediment distributed model to express the probability that eroded particles mobilized from an individual cell are transported to the nearest stream pixel (Stefano et al., 2005).

$$NSL_i = GSL \times SDR_i \tag{3}$$

where GSL is the RUSLE amount of soil loss at a pixel size (in t/ha/yr) and SDR_i is the SDR at the pixel scale.

$$SDR_i = \exp\left(-\beta * \frac{L_i}{R_i(S_i)^{1/2}}\right) \tag{4}$$

where β is a routing coefficient set −0.0051; L_i is the length of segment i in the flow path and is derived from the length of the side or diagonal of a cell depending on the flow direction in the cell (in m). In the LAMPT_Mo, L_i is the flow length layer imported as the initial input (see the LAMPT_Mo description). R_i is the coefficient of surface roughness characteristics (m/s) derived based on the look-up table (Table S1). S_i is the slope gradient (m/m) generated from the surface slope (Eq. (5)).

$$S_i = \tan(\alpha + 0.01) \tag{5}$$

where α is the surface slope (in degree) derived from surface elevation model as detailed in Diwediga et al. (2015).

The roughness of the earth surface, i.e., land surface cover (e.g., roads, ground) and the objects hereon (e.g., buildings and vegetation) are of important interest in terms of hydrodynamic friction (Dorn et al., 2014) and therefore affect water flow and sediment transport as well as re-deposition on the landscape under investigation (McCuen, 1998). Roughness reflects the influence of the surface on the momentum and energy dissipation in resisting the flow of the fluid (Galema, 2009). Manning's roughness coefficient is the most common parameter used to express surface roughness in surface hydrological processes (Kalyanapu et al., 2009; Tamene et al., 2014).

2.4. Description of scenarios and simulation outputs

Two categorical scenarios were defined (Fig. 3): (i) simulations based on business as usual (S0) conditions, and (ii) simulations based on LUC management options (S1). For all scenarios, simulated soil loss is analyzed to highlight the contribution of specific LUC types, slope-classes, and river buffer zones to soil erosion. Most of the scenario designs result from LUC-reorganization at the landscape level to identify viable options that significantly reduce soil loss (Tamene, 2005; Tamene et al., 2014). In all the scenarios proposed in the LAMPT_Mo, default values of model variables are offered according to the conditions in the Mo river basin. Nevertheless, large ranges of values are provided to select the appropriate design of conservation in specific sites and when facing uncertainties related to the selection of values (Tamene et al., 2014). Values of the different variables are detailed in the Supplementary file.

2.5. Approaches for model evaluation

In inaccessible mountainous areas, data scarcity is a crucial problem to the assessment of land degradation. Most often, data requirement for calibrating and validating preliminary studies is a big challenge. In Mo river basin, the situation is similar and tremendously hectic because measurement networks for quantifying the effects of different factors on soil loss are still lacking. To overcome this data paucity and propose the first soil erosion model for rural landscapes in Togo with the case of Mo basin, a triangulation of four approaches is used to evaluate the model outputs and performance.

First, the evaluation by construct approach was used to discuss the validity of the entry data, and hence evaluate the output information. It is assumed that in a process-based and spatially distributed model, input data of good quality yield acceptable modelling outputs. We then discussed the model inputs for the evaluation of the model outputs. We assumed that the results from our model are acceptable and hence compared them with general soil erosion data range over West Africa and other similar mountainous environments of Africa (Symeonakis and Higginbottom, 2015) and with the tolerable soil loss as well (Roose, 1976; Le et al., 2012). We founded this first approach on the principle that similar environmental constraints yield similar range of soil erosion phenomenon (Tamene and Le, 2015). Then, this evaluation of the model outputs by comparison with data ranges from the surrounding West Africa and sub-Saharan environments (Le et al., 2012; Roose, 1976; Schmengler, 2010; Tamene et al., 2014) allowed to judge the level severity of soil erosion in Mo river basin. In addition, the model outputs are compared with the soil loss threshold of 10–12 t/ha/yr for the Tropics (Palmer, 1991).

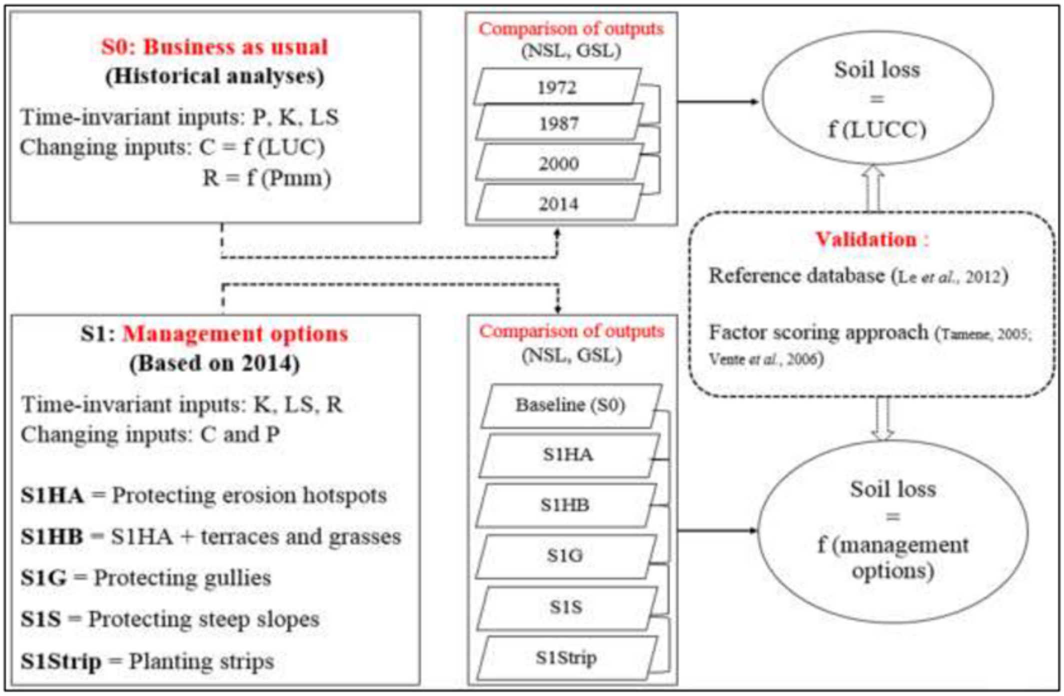

Fig. 3. Scenarios of land management implemented in LAMPT_Mo. Note: LUC = land use/cover types; LUCC = land use/cover change; GSL = gross soil loss; NSL = net soil loss; R = rainfall erosivity factor; P = land management practices factor; K = soil erodibility factor; LS = slope length coefficient; C = soil cover factor.

Next, since the purpose of the soil erosion model is not exclusively the quantification of the amount of NSL, but also the capability to provide erosion severity patterns helpful to adopt adequate management options (Le et al., 2012; Tamene et al., 2014), the current study also aims at providing a most plausible delineation of erosion severity patterns at the Mo landscape level. Hence, a semi-qualitative approach was used, through selective field observations in the study area, to evaluate the quality of soil erosion in the field with the simulated outputs. Field scoring and ranking of erosion factors, and evidence of soil erosion were used for that purpose (Tamene et al., 2006). Since each natural spatially explicit phenomenon is a result of an association of factors, it is assumed that scoring such factors or association of factors can help in representing such phenomena. The approach consisted of ranking and scoring individual potential factors of erosion sensitivity during field visits. Prior to the field visits, two hydrological sub-units (Tchamou and Boualé catchments) derived using elevation data for the Shuttle Radar Terrain Mission (SRTM) and drainage networks (Tamene, 2005) were selected based on their accessibility and heterogeneous characteristics. Then, the list of landscape features describing on-site (GSL) and off-site (NSL) soil erosion was used to characterize each of the selected sites to match the model outputs and the field observations. Further, the total score was calculated for each site and compared with the GSL and NSL using regression trends. This approach of field characterization is widely used to validate soil erosion models (De Vente et al., 2005; Tamene, 2005). Results from the two sub-units could be extrapolated to the entire Mo basin, assuming that sites with similar characteristics undergo similar range of erosion risk potential as described by the concepts of similar environmental constraints envelopes (Tamene and Le, 2015).

Finally, similar to techniques used to assess local perceptions on environmental problems (Brunner et al., 2008; Okoba and De Graaff, 2005), the study used focus group discussions and participatory rural appraisal to indirectly evaluate the model outputs. This approach is a kind of on-site ground truthing used for the evaluation of environmental changes by the rural community people (Vila Subirós et al., 2016). Farmers, local agricultural extension agents, and local leaders in seven rural communities (Aledjo-Kadara, Aleheride, Kolina, Amaide, Sagbadai, Koumoniode and Bouzalo-Tabalo) were asked through focus groups and individual interviews, to judge and map the severity level of soil erosion in their landscapes using certain indicators such as hills, rivers, and bare surfaces. The focus groups were composed of 6, 8, 5, 7, 7, 8, and 9 people for the seven communities, respectively. In addition, 101 farmers which are direct land users, were interviewed. They were randomly selected based on their availability since the survey was conducted during intensive farming activities in the visited communities. The survey was conducted during the rainy season to help farmers to better understand and appreciate the soil loss phenomenon. In supporting this process, the modelled soil erosion severity was presented and explained, and feedback was obtained from groups on their reactions. However, since quantification was a problem, erosion patterns were drawn on a qualitative basis.

3. Results

3.1. Historical soil loss in the Mo basin: business-as-usual (BAU) scenario

The spatial patterns of the historical GSL and NSL in 1972, 1987, 2000, and 2014 in the Mo basin are shown in Fig. 4. Generally, an increasing trend of the average GSL values was observed at landscape level. The simulated GSL was of 160, 175, 186, and 279 t/ha/yr for the 1972, 1987, 2000 and 2014, respectively. These patterns proportionally aligned with the historical configuration of LUC in the basin. The adjustment of the GSL with the SDR (average values of 5–6%) showed that the NSL patterns are highly influenced by the river/stream network in the catchment (Fig. S1). Consequently, the average NSLs were of 26, 23, 27, and 44 t/ha/yr, respectively for 1972, 1987, 2000, and 2014. These results generally showed an increasing trend in NSL over time. LUC change inducing vegetation decline exhibited increasing GSL, suggesting that high soil loss is associated with poor land cover. It is therefore evident that the vegetation cover is important factor controlling on-site soil erosion, as increasing vegetation loss resulted in substantial increase in soil loss over time.

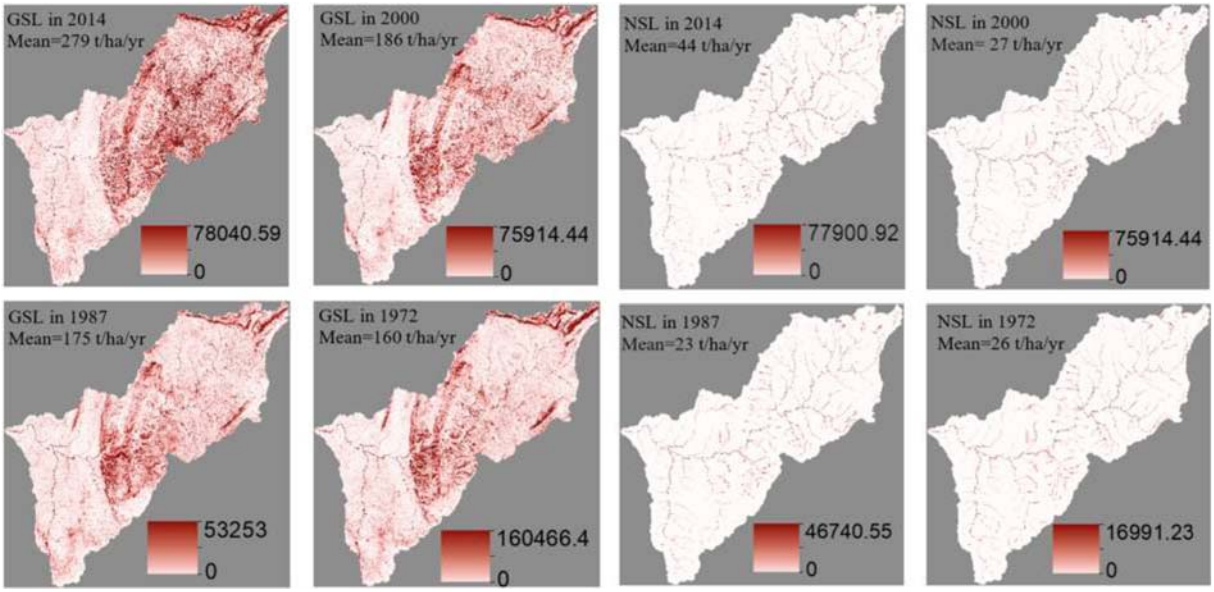

Fig. 4. Spatial patterns of simulated historical GSL and NSL for the Mo basin.

3.2. Field-based characterization and participatory evaluation of soil erosion patterns

Field characterization shows poor agreement with the predicted NSL and GSL for both the sub-units and the entire catchments (Table 1). However, the GSL showed better agreement with the factor scoring approach (FSA) outputs while differences between Boualé and Tchamou suggest heterogeneous patterns of soil loss in the Mo landscapes. The low agreement may be due to two main reasons. First, there could be biases in the scoring of soil erosion evidence which could reflect when compared with the modeled NSL. Second, the sediment routing approach that only considered the flow path to a river, affecting the SDR, induced biases in computing the NSL. Terrain attributes such as soil types, which are specific to each site may also explain differences in the NSL outputs. However, the positive correlations suggest that the model mimics the landscape behavior despite its heterogeneity. The FSA, however, suggests that soil erosion is a real phenomenon occurring in the Mo basin with different spatial patterns.

From the perspectives of rural communities' perception and evaluation of soil erosion, all respondents recognized that soil erosion is a landscape-wide phenomenon. The most erosion-prone areas mentioned by rural communities are riverbanks (73.27% of respondents), steep slopes on hillsides (86.14%) and bare soils (65.35%) (Table 2). During the focus group discussions, surface leaching was mentioned as the most prominent erosion manifestation, either in farmlands or in wildlands. This result reveals the need to analyze soil erosion in accordance to slope classes, land cover types, and classes of distance to rivers in order to identify critical zones requiring intervention.

3.3. Distribution of historical net soil loss in relation to environmental units

The NSLs were analyzed in relation to three environmental units: slope, LUC and proximity to rivers. Steep areas (slope ≥ 15°) contributed more to the average annual sediment yields (Fig. 5). Areas with lower slopes (<15°) yield NSLs lower than 10 t/ha/yr while lands with slopes between 5 and 10° globally experienced NSLs lower than 5 t/ha/yr. Higher NSLs experienced by flat terrain (<5°) compared with 5–10° class can be explained by the impacts of human settlements and agricultural fields in UPAs and the vulnerability of soils to erosion in PAs (see the K factor map with higher erodibility in PAs; Fig. S1). This suggests that surface cover reduction due to human activities increases soil erosion vulnerability, ascertained by the NSL distribution according to LUC types (Fig. S2). This Fig. S2 shows that savannahs and croplands experience the highest NSL over time, with an increasing NSL when canopy cover decreases, ranging from the lowest average values of 2–4 t/ha/yr in forests to 16–34 t/ha/yr in farmlands. Apart from the buffer 0–50 m, the proximity analyses show a historical increasing NSL trend for all distance classes, though the range of the average NSL (7–9 t/ha/yr) did not show much change. The closest 50 m to rivers/streams yields a very large NSL (79, 76, 70, and 66 t/ha/yr, respectively for 1972, 1987, 2000, and 2014), while the farther distances to rivers experience a sharp, lower average NSL. The other aspects related to the model outputs are discussed in the Supplementary File.

3.4. Land management scenarios for erosion control in the Mo basin

On one hand, in reference with the baseline, the scenarios targeting the gullies (42 t/ha/yr) and the development of strips (41 t/ha/yr) were less efficient for the NSL reduction in the landscape (5 and 7%, respectively) (Fig. 6). This is probably because steep slopes are quite stable over the landscape, which is more under protected status. The NSL is marginally sensitive when strips of 100 m are planted interlined with natural stands of 100 m, suggesting the inefficiency of this management option. Meanwhile, three options were efficient: S1S, S1HA, and S1HB. S1HA and S1HB induce a significant reduction in the NSL to approximately 15 and 13 t/ha/yr, respectively. The efficiency was an approximate 66 and 77% reduction for the S1HA and S1HB, respectively. However, the quite similar effects of S1HA and S1HB are due to the

Table 1
Correlation coefficients between the sum of field scores and predicted soil loss.

Hydrological units	GSL	NSL
Mo basin ($n = 87$)	0.135	0.133
Tchamou unit ($n = 36$)	0.225	0.011
Boualé unit ($n = 51$)	0.413	0.344

Note: “n” = number of field points characterized during the factor scoring approach; GSL = gross soil loss; NSL = net soil loss.

Table 2
Perceptions of erosion-prone areas in seven rural communities in the Mo basin.

Responses	Steep lands	Poor covered lands	Waterways and banks	Sandy soils
No	13.86	34.65	26.73	65.35
Yes	86.14	65.35	73.27	34.65

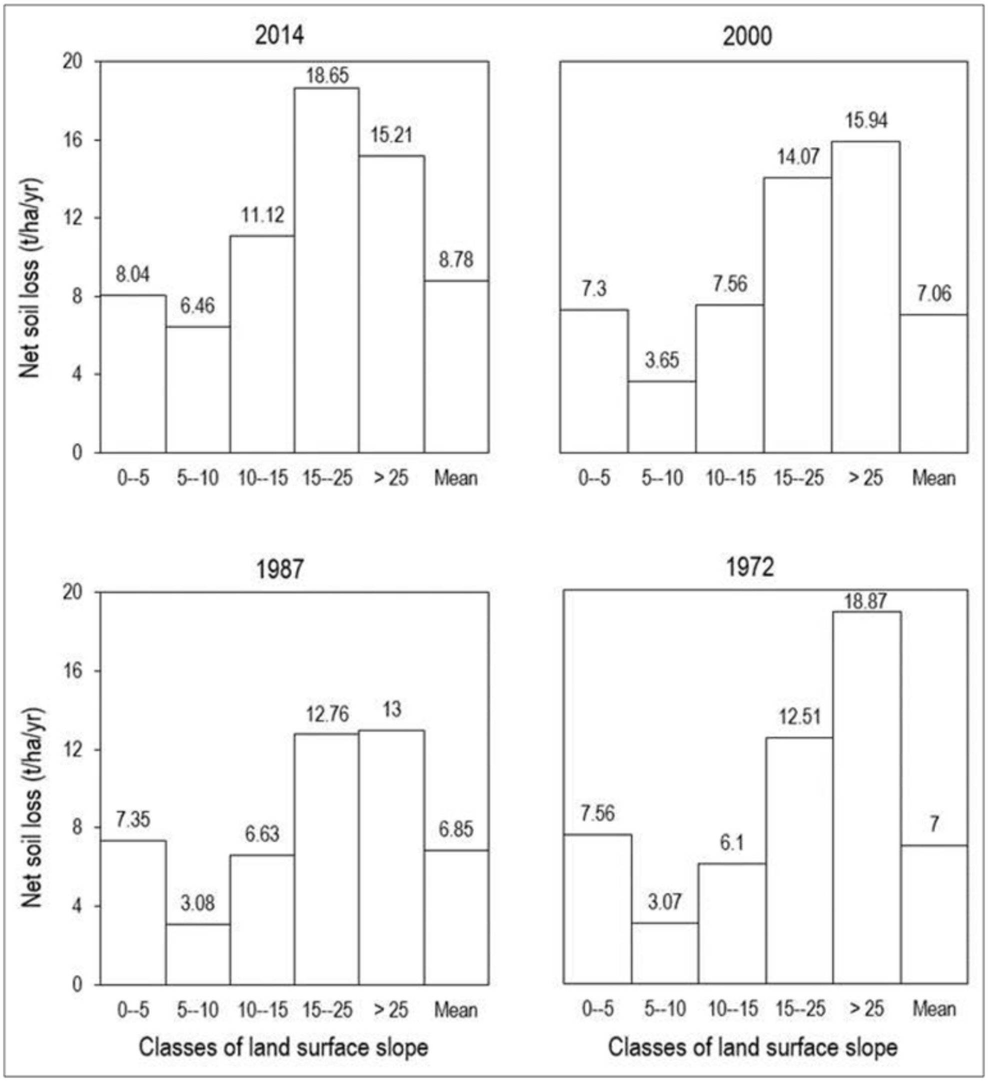

Fig. 5. Historical NSL per slope classes (in degree) for the Mo river basin.

fact that less erosion hotspots are located within gullied areas. Outputs from S1S suggested that steep slopes (≥15°) contributed to about 64% of the total NSL in the Mo basin (reduction from 44 to 16 t/ha/yr). In a similar study, Galdino et al. (2015) found that management of pasture areas with terraces and sloped areas with native vegetation contribute to significant reduction of the erosion rate. Large proportions of erosion hotspots are located on slopes ≥5° all over the Mo landscape, aligning with the outputs from focus group discussions, from which soil erosion occur predominantly on steep slopes and bare soils. This suggests that land management options targeting the protection of gullies and planting strips are less-efficient, showing the importance of selecting the appropriate measures for soil conservation interventions.

On the other hand, the analysis according to riverside buffers showed that the options S1HA and S1HB had significant NSL reduction in 50 m river buffer zones (Fig. 7). However, the soil loss within the 0–50 m buffer remain quite high due to the fact that these areas are more sensitive to erosion, especially lateral erosion. Further analyses of the management effects on NSL distribution according to LUC types showed that the reduction of NSL in forest areas is almost 100% for the options S1HA, S1HB, and S1G (Fig. S4). The average NSL in forested areas declines from 4 t/ha/yr to almost 0 t/ha/yr (not absolute 0). Further details on the effects of the management options on NSL distribution according to the environmental units are provided in the Supplementary File.

4. Discussion

4.1. Evaluation of LAMPT_Mo tool

LAMPT_Mo tool estimates of soil loss in Mo Basin amount to 26, 23, 27 and 44 t/ha/yr, respectively for 1972, 1987, 2000 and 2014. Because of the lack of measured data specific for the Mo basin, the accuracy of these outputs is hard to evaluate, and therefore we discussed the input data and compared the model outputs with other similar case studies. With regard to the input data used to compute the soil cover factor C, the land cover maps of good accuracies useful for model inputs (Diwediga et al., 2017b) as their ecological characteristics were successfully depicted through the combined analysis of remote sensing and ecological data in the area (Diwediga et al., 2015). With regard to R factor, derived based on gridded rainfall data covering the study area (Diwediga et al., 2017a), was usefully developed and used in several studies over West Africa (Le et al., **2012**; Tamene and Le, 2015; Diwediga et al., 2017a). Even though the usage of local weather data might be considered to produce more accurate R factor, it is important

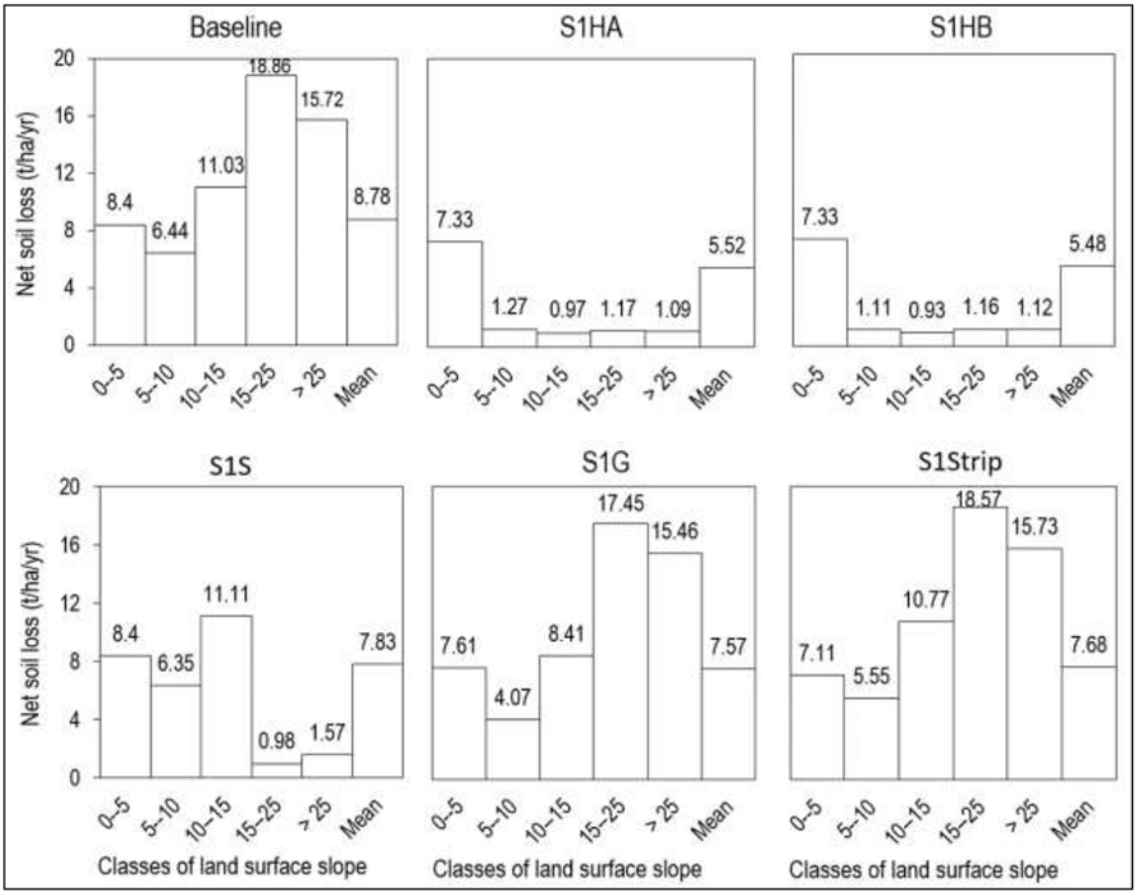

Fig. 6. NSL for different land management scenarios compared to the baseline conditions. Note: on average, NSL at basin level are the following: baseline = 44 t/ha/yr; S1HA = 15 t/ha/yr; S1HB = 13 t/ha/yr; S1S = 18 t/ha/yr; S1G = 42 t/ha/yr; S1Strip = 41 t/ha/yr.

to highlight that data paucity (due to lack of weather station) combined to the gaps in data records in the available stations compels to the reliance on available regular spatial and gridded data. Furthermore, it is most often encouraged to use rainfall intensity data that produce more reliable R factor. Slight investigation of the relationship between rainfall (variation between 1060 and 1120 mm) affecting the R factor revealed that soil erosion is sensitive to rainfall variability with a linear relationship (Fig. S7). However, the magnitude (3.94 t/lha/yr) cannot affect the decision regarding land conservation initiatives, as we argued that measures would be developed based on erosion severity classes. For instance, priority for conservation measures required for a soil erosion hotspot of 45 t/ha/yr will be the same for hotspots of 50 t/ha/yr or higher. It is important to mention that increasing rainfall as consequence of climate change effects may affect the erosion intensity in the basin and raises therefore concerns with regard to planning perspectives.

Based on the principle of evaluation by construct, the accuracy level of the model inputs, such as LUC types (ranging from 69 to 92%) (Diwediga et al., 2017b) and soil erodibility (Le et al., **2012**), and the landform-based inputs (Fig. S1) are satisfactory for modelling (Aguirre-Gutiérrez et al., 2012; Leh et al., 2013; Monserud and Leemans, 1992). Thus, NSLs for the Mo basin are quite reliable to guide decisions for soil erosion monitoring.

4.2. Soil erosion patterns in the Mo River

In comparison with similar studies over West Africa, the simulated results in this study lie within the soil loss ranges over West Africa (Le et al., 2012; Tamene and Le, 2015) and similar mountainous environments of Africa (Symeonakis and Higginbottom, 2015; Tamene et al., 2014). The NSL of 2014 is quite high and compared with the modeled value obtained (35 t/ha/yr) for the White Volta sub-basin in West Africa (Le et al., 2012; Tamene and Le, 2015). However, field measurements in some sub-catchments of the same White Volta basin showed that the simulated NSLs of the current study were quite high and up to the double of the values measured at Doba, Zebila, and Bugri (19, 27, and 18 t/ha/yr, respectively). The relatively high NSL of this study could be due to two intrinsic factors: the natural conditions (roughed landform and high rainfall) compared with the Sahelian environments, and the sediment routing approach used to adjust the GSL to NSL (Gallant and Wilson, 2000; Tamene et al., 2006). Derived from the Multiple Flow Direction (Freeman, 1991), the flow path length was a function of the stream network heavily developed in the mountainous Mo basin. Furthermore, higher amounts of NSL were expected, but the large size of the watershed could have induced a loss of sediment into pits/sinks all over the watershed (Shi et al., 2014). However, in comparison to the tolerable soil loss of 12–15 t/ha/yr (Roose, 1976; Le et al., 2012), the current study yielded a high NSL (over 25 t/ha/yr), although there are protected areas. This could be due to the relief of the basin, which causes high sediment yield, even in PAs. This result suggests the need to promote sustainable land management practices for reducing soil erosion at the landscape level.

LUC change inducing vegetation loss showed increasing GSL, suggesting that high soil loss is associated with poor land cover (Feng et al., 2010; Zhou et al., 2014). It is therefore evident that the vegetation cover is important in reducing on-site soil erosion (Feng et al., 2010; Lal, 1993). Similarly, Meshesha et al. (2012) found that the vegetation degradation resulted in substantial increase of the amount of soil loss

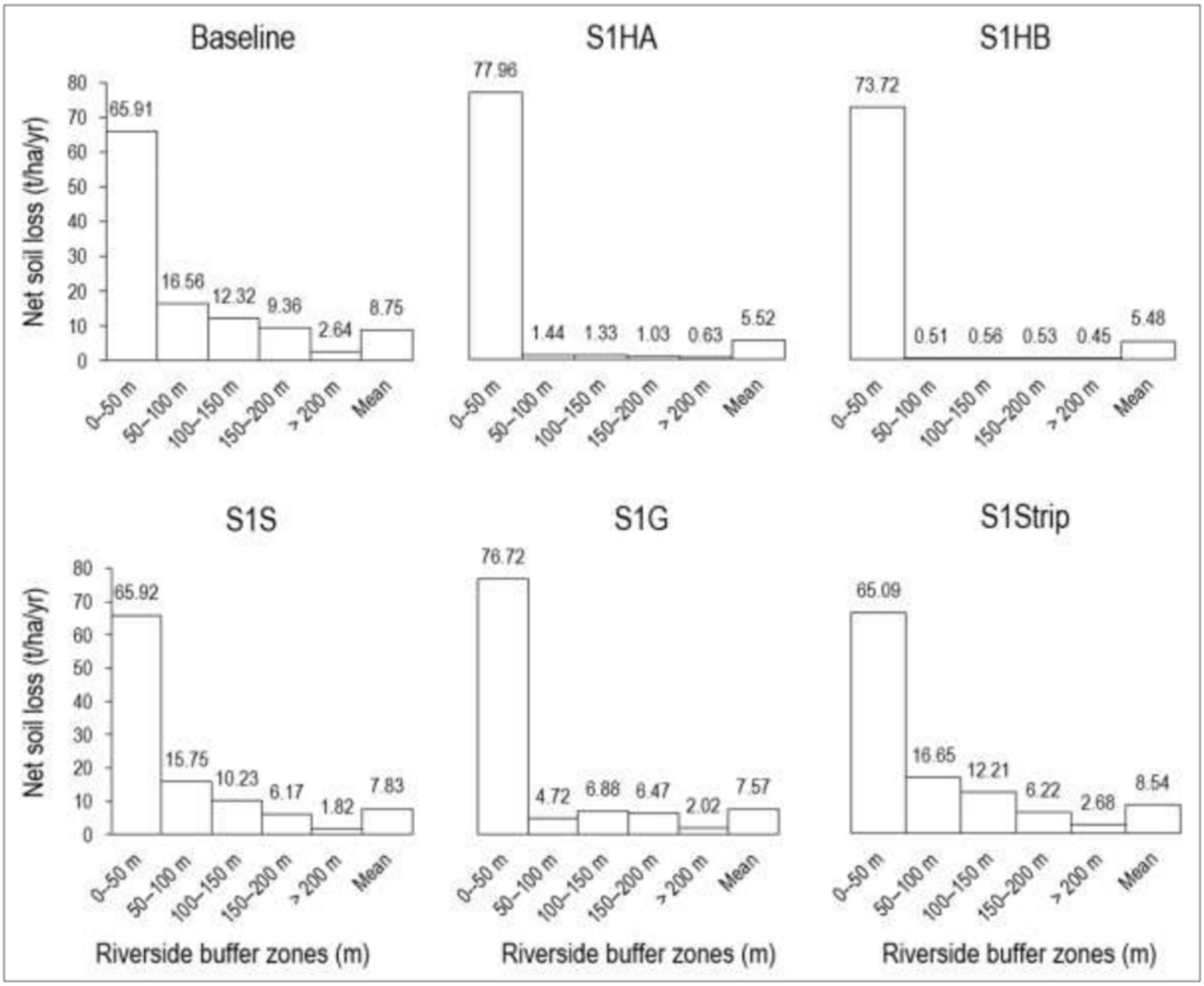

Fig. 7. NSL according to riverside buffer zones for different management scenarios. Note: on average, NSL at basin level are the following: baseline = 44 t/ha/yr; S1HA = 15 t/ha/yr; S1HB = 13 t/ha/yr; S1S = 18 t/ha/yr; S1G = 42 t/ha/yr; S1Strip = 41 t/ha/yr.

over time. In this regard, conservation practices aiming at increasing vegetation cover have a decreasing effect on the erosion rate compared with the baseline situation (Ligonja and Shrestha, 2015).

4.3. Implications for sustainable land management and soil conservation in the Mo River basin

In the Mo river basin, landscape degradation because of the combination of human and natural conditions is evident and affecting the soil ecosystem services, including soil nutrient availability and soil protection (Diwediga et al., 2015; Diwediga et al., 2017a). In the context of this study, LAMPT_Mo tool led to a good appreciation of soil erosion patterns in response to landscape conditions. The stratification of erosion hotspots revealed that areas with less vegetation cover were vulnerable to erosion. It is evident that the vegetation cover significantly influence sediment yield at landscape level, as it plays an important role in adjusting the sediment detachment and the hydrological behavior involved in sediment transportation (Siepel et al., 2002). This suggests that based on identified hotspots with regard to poor vegetation cover management options of reforestation and forest restoration should be promoted in order to abate soil erosion (Zhou et al., 2014; Hao et al., 2004; Boardman et al., 2003). On the other angle, steep slopes (> 15°) showed high prevalence of soil loss. Similarly, Nabi et al. (2017) suggested that soil and water conservation measures targeting steep slopes significantly reduce soil loss at watershed level. This implies that comprehensive soil conservation measures should be developed to control erosion on steep slopes and prevent sediment delivery to rivers (Haiyan and Liying, 2017; Gashaw et al., 2017). Further similar efforts should be undertaken to stabilize fragile riversides with protective measures in order to reduce gully enlargement and river siltation.

As LAMPT_Mo offers an open and user-friendly interface, it can be easily transferred to local stakeholders to design and examine different land management pathways of their preference to select proper, feasible, cost-effective and up scalable conservation measures. Thus, it offers opportunity for developing a wide portfolio of possible management pathways, contributing to the achievement of Land Degradation Neutrality initiatives through different innovative land management options. This capability can offer way for upscaling findings based on landscape similarity concept (Tamene and Le, 2015) and tool customization in similar landscapes and river basins. Therefore, some ways forward to offer integrative and more promising planning and management tool could be the integration of other ecosystem services (soil carbon dynamics, nutrient flows, etc.) and ecosystem value changes (impact assessment in economic perspectives). On the implementation perspectives, economic analysis in terms of cost-benefit analyses could be investigated with regard to the different management options for efficient and optimization in resources mobilization.

4.4. Limitations of LAMPT_Mo and recommendations for future analyses

Due to spatial variability, data availability, and many other factors, model inputs always carry uncertainties related to input data (Lenhart et al., 2002). This might be pertinent for the Mo River basin, especially with recurrent scarcity data in terms of measured and reference studies.

As this study is probably the first attempt at mimicking soil erosion using such a model in the multifunctional landscapes of Mo River basin, which referred to data range from West African environments, it suggested that specific and historical field measurements could have induced more positive impacts on soil erosion measurement in Mo basin (Tanyas et al., 2015). The modeled sediment yield was within the range of values reported in similar studies in West African environments and humid tropics with similar environmental conditions (Tamene and Le, 2015; Tamene, 2005; Le et al., 2012; Roose, 1976). However, to guide future developments of the model, the following limitations need to be overcome. First, the necessity of direct measurements of soil loss is of great interest for research on real phenomena, even though the paucity of such data is often a constraint compelling the use of models to represent the influence of soil and vegetation management on soil loss in humid tropics (Labriere et al., 2015) and poorly accessible regions (Tamene and Le, 2015). It is therefore suggested that this initial study should be supplemented by long-term field observations to capture the real behavior of soil erosion processes at the landscape level, considering all landforms and land use/cover units as well as sediment fate measurements at the basin outlet or dams (e.g. Tamene, 2005; Hiepe, 2008; Schmengler, 2010). Second, perspectives of erosion modelling should rely on input data more specific to the study area to avoid the over- or under-representation of soil erosion (Tanyas et al., 2015; Yang, 2014). Our model did not used measured data such as rainfall from local weather stations, and specific P factor for possible land management units in the study area. In addition, further sensitivity analyses are needed to improve the detection of the relationships between the individual model inputs and the outputs. This is critical as in our current model, sort of linear relationship might exist between the soil loss and the inputs, especially the R factor (see Fig. S7), even though the spatial patterns of rainfall are not of linear type over time in the study area (Badjana et al., 2011). It is important to detect the most sensitive input parameters that might be potentially climate-driven, and relevant to guide more efficiently the design for management interventions (Sanchez-Canales et al., 2015). Third, though it is important to promote participative methods in ecosystem services assessment (Vila Subirós et al., 2016), another limitation of the study resides in the fact that the participatory evaluation approach could not consider quantitative aspects to fully appreciate the modelling outputs because of rural people's incapacity to quantify. In overall, these limitations suggest that additional analyses are necessary in order to provide more robust tool and interpret the quantitative inputs and outputs with more confidence.

5. Conclusion

The goal of this study was to simulate the spatial patterns of historical soil erosion hotspots and the efficiency of sustainable land management options in Mo River basin in Central Togo. A landscape management tool and planning was used as spatially explicit tool based on RUSLE model to simulate soil loss and investigate the patterns/processes under different management units (slope classes, LUC types, the distances to rivers, land protection regimes) and management options. The study found that soil erosion estimates from 1972 to 2014 increased following the spatial-temporal patterns of LUCC and landform. The average annual sediment yields for the Mo basin were approximately 26, 23, 27, and 44 t/ha/yr, respectively, for 1972, 1987, 2000, and 2014. The soil erosion did not show an even spatial pattern; highest soil loss areas were located on steep slopes (≥15°), and more seriously in areas with low vegetation cover, such as savannah and croplands, and in areas closer to riverbeds (distances ≤100 m). These estimates were quite high compared with the values obtained by several studies in West African environments. These differences could be caused by the different methodological approaches, the contextual natural settings (mountainous environment of Mo basin, high rainfall), and human influence (possible diversity in land management practices). On the management perspectives, various options showed that erosion can be reduced by adopting conservative and restoration measures in erosion hotspots. The study revealed that planning and management measures targeting the enclosure of erosion hotspots can potentially reduce soil loss up to 90% for slope classes of 5–10° and 15–25°. The application of this erosion model in the Mo basin showed sufficient insights in identifying soil erosion-prone areas and judging the severity of the average soil loss in comparison with tolerable limits. The particularity of this model was its capabilities to integrate soil erosion dynamic in relation with LUC types and landform features and to generate timely spatially explicit information. The novelty of the research resides in the integration of rural opinions in the assessment of the final simulation outputs. This integration of rural opinions is of great importance, as it could be favorable to the collaborative implementation of sustainable management options. Further research on the methodological approaches that integrate (1) the co-design of innovative and cost-effective management options emanating from local land managers and users, and (2) the temporal distribution (at least on monthly basis), can provide critical information on the holistic perspective for soil erosion alleviation.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2017.12.228.

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